Block Based Image Segmentation

Md. Mahmudul Hasan[1], Shaila Sharmeen[1], Md. Anisur Rahman[1], M. Ameer Ali[1], and Md. Humayun Kabir[2]

[1] East West University
[2] Bangladesh University of Engineering and Technology
{shailacse2k,mhkabir}@gmail.com,
ameer7302002@yahoo.com

Abstract. Image segmentation is an important research field due increasing Internet and computer based applications and also for video coding but it is very challenging. There exist a huge number of algorithms for image segmentation using split and merge having some limitations for which pattern based object segmentation using split and merge (PSM) was proposed to overcome the problems of basic split and merge (SM) algorithm being unable to segment properly all types of objects in an image due to huge variations among the objects. Addressing this issue, a new algorithm namely block based image segmentation (BIS) algorithm has been presented in this paper considering multi stage merging technique. The experimental analysis proves the superior performance over the existing algorithm.

Keywords: Image segmentation, pattern based image segmentation, fuzzy clustering.

1 Introduction

Image segmentation is an image processing technique to separate mutually exclusive homogeneous regions of interest of an image. Segmenting objects in an image plays a fundamental role in the field of image processing and image analysis. Segmenting objects in an image is a very difficult and challenging task due to huge number of objects and the variations among the objects in terms of color, intensity and locations [1].

Many algorithms and techniques for segmenting objects in an image exist in the literature [1-7]. Those algorithms and techniques can roughly be categorized into two categories: (i) Boundary-based methods and (ii) Region-based methods. In boundary-based methods, an object is segmented by utilizing the discontinuity of pixel intensity in an image and tends to partition an image by detecting isolated points, lines and edges according to abrupt changes. Region-based methods include the techniques of clustering, region growing, and regions splitting and merging. These algorithms exploit the homogeneity of spatially dense information such as intensity, color, texture etc. Boundary based algorithms given in [2,3] are not efficient due to following reasons: (i) these algorithms do not exploit spatial information, (ii) these

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algorithms are domain dependent, (iii) thresholds used in these algorithms are manually set, (iv) two adjacent regions do not share the same boundary information in these algorithms. Region-based algorithms proposed in [4-6] are much more efficient than the boundary-based algorithms. Split-and-merge (SM) of [6] is a popular, easy, and simple region-based algorithm to segment objects in an image. To overcome the problem associated with Basic SM algorithm and its several variations a new algorithm called pattern based object segmentation using Split-and-Merge (PSM) was proposed in [7] using pattern matching for object extraction. However, the biggest drawback of PSM algorithm is that it cannot segment the homogeneous regions that are connected. In this paper, we propose a new algorithm block based image segmentation (BIS) taking into account the basic SM algorithm, image feature stability, inter- and intra-object variability and human visual perception. The experimental analysis has been conducted on gray-scale images considering the intensity of pixel as the feature for segmentation. The results of the BIS algorithm are compared with that of the PSM algorithm [7], basic SM algorithm [6], classical fuzzy clustering algorithm namely suppressed fuzzy c-means (SFCM) using combination of pixel intensity and pixel location as the feature for segmentation process [10], and the newly developed shape based clustering algorithm called object based image segmentation using fuzzy clustering (OSF) [1]. The BIS algorithm performs better than all the algorithms mentioned above in segmenting connected regions and producing less distortion.

The rest of the paper is organized as follows: the basic SM algorithm and the supporting literature containing the theorems applied to propose BIS algorithm is detailed in section 2**,** while the proposed BIS algorithm is presented in Section 3**.** Computational complexity is calculated in Section 4. The experimental results are described in Section 5 and finally some concluding remarks are provided in Section 6.

2 Supporting Literature

In this Section, we describe related research works those are directly used to propose the object segmentation algorithm called block based image segmentation (BIS).

2.1 The Split and Merge (SM) Algorithm

The split-and-merge (SM) algorithm, developed by Pavilidis [6,11] in 1974, is still one of the most popular classical image segmentation algorithms and is widely used directly or indirectly in image processing while the details and summarized steps of SM algorithm are given in [7].

2.2 Region Stability

Region stability test is applied in both the split and merge stage. A region is said to be stable if it does not contain portion of more than one object. Region stability is measured depending on whether all the samples in a sample space (here, pixels in a region) belong to the same sample space (here, the same region) or not. If the regions are unstable, they are subdivided into several smaller regions or sample spaces. In this purpose, T-test has been applied because of its world wide appeal [7].

2.3 Segmentation Using Patterns

Patterns were first successfully used in [8, 9] to find motion vectors of the objects (micro blocks) in video encoding. A video frame is segmented into one or more moving object using 16X16 blocks, called micro-blocks (MBs). Wong *et. al.* [15] compare each micro-block with the patterns to find whether there is any moving object in the micro-block under consideration. A match with any pattern indicates a moving object's presence in the micro-block. This matching technique of marco blocks are taken into consideration and developed a new segmentation algorithm in [7].

2.4 Multistage Merging Technique

A single criterion for the complete segmentation process causes a dissatisfactory segmentation results. This has motivated Faruquzzaman *et. al.* [12] and Brox *et. al.* [13] to use a multi-stage approach in which a criterion is used as long as it can well handle the current configuration. Then the criterion is replaced by another one. They have used T-test for both splitting and merging. They also considered intra-region variance minimization and inter-region variance maximization throughout the merging process to maintain object identity. The technique of human visual perception limitation was used to maintain the realistic shape of the identified object.

2.5 Intra-variance and Inter-variance Test

Merging regions using only T-test may not give satisfactory result. This may produce more number of regions than the number of objects in an image. Another merging stage called Intra-variance and Inter-variance Test can optimize the number of regions. The optimal result tends to minimize intra-region variability and maximize inter region variability [12]. To minimize the intra-region variability, the sum of squared error criterion is used such that it fits better to the model. Further, it implements the joint intra-region variability constraint as a minimum variance for the union of two clusters. At the same time, joining two clusters maximizes the inter cluster variability [12].

2.6 Concept of Human Visual Perception

If the change of any object or feature is less than or equal to $0.5dB$, human perception is unable to detect the change and the details of this is explained in [1].

3 Proposed Model

This Section presents a new algorithm for image segmentation, namely block based image segmentation (BIS) algorithm, which is developed to overcome the various segmentation faults of the PSM algorithm. The proposed BIS algorithm is divided into following stages (i) split stage, (ii) region accepting stage, and (iii) merge stage. The basic assumptions for the BIS algorithm are as follows: (i) the aspect ratio of the image is 1.33 or 4/3 with the image size 1024X768, (ii) the image is segmented into square regions in sizes 16X16 blocks, and (iii) only the foreground pixels are segmented and the back ground pixels are set to zero.

3.1 Split Stage

An image is divided in the split stage in two steps: (i) Split Stage - 1, and (ii) Split Stage - 2. The region stability test is applied in both steps to decide whether the region is stable or not.

Split Stage – 1: In this stage, T-test is applied first on the original image of size 1024×768 .If the image is found unstable it is subdivided into 12 equal and square sub-regions [7].

Split Stage – 2: After the completion of the split stage-1, split stage-2 is applied. In this stage each square region is recursively subdivided into 4 sub-regions by applying the T-test.

After completing of the split stage, the regions are matched with the patterns called micro-blocks (MBs) in region accepting stage which is detailed in the following section.

3.2 Region Accepting Stage

In the split stage, the square regions of different length are produced $R_1, R_2, R_3, \ldots, R_n$ where n is the number of the splitted regions. The splitted regions are matched with the patterns of the pattern codebook described in Section 2.3. We use the technique of pattern matching from [7]. If the size of the MB is $a \times b$, the percentage of matching of a region R_i with any pattern P_j can be calculated using the following equation:

$$POM(\%) = \frac{\sum_{x=1}^{a} \sum_{y=1}^{b} f(x, y)}{a \times b}$$

If $POM(\%) \geq 95$ the pattern P_j is said fully matched with the region R_i .If $60 \leq POM(\%) < 95$ the region is said to be partially-matched with the pattern P_j and if $POM(\%) < 60$, pattern P_j is unmatched with the region R_i . Region accepting stage find three types of regions: accepted region, partially accepted region, and rejected region. Accepted region is the region that contains only foreground pixels while partially accepted region has pixels of both foreground and background. The partially accepted regions need to be replaced by the best match pattern and after replacing it will be treated as an accepted region. The rejected region is the background of the image and is not being replaced by a matched pattern. Region accepting stage uses following two steps to mark accepted region and not accepted region:

Step-1: If a region has size greater than the size 16×16 of a micro-block and does not contain any background pixels, then the region is marked as accepted, otherwise, it is marked as rejected.

Step-2: When a region size is equal to the size of the MB, then the regions may be accepted or partially accepted or rejected. If the region does not have any background pixels, it would be treated as accepted region while the rejected block contains only background pixels. On other hand, a region having both background and foreground pixels, is considered as the partially accepted region and in this case, it need to match this region with the given patterns. This region will be replaced by the best match pattern and then this replaced block will be treated as the accepted region. This process will continue for all the regions whose size is equal to that of the MB.

Two regions are selected for merging using multistage merging technique if they are connected and accepted. The merging stage is detailed in the following Section.

3.3 Merge Stage

In the merge stage of the BIS algorithm, only connected and accepted regions are considered to be merged. Since the single stage merging technique does not give us satisfactory result, multistage merging technique is applied in BIS as discussed in Section 2.4. The merge stage of the proposed BIS algorithm contains three main constituent parts which are applied only on the accepted and connected regions. These are: (i) merging on the basis of T-test, (ii) merging for inter-variance maximization and intra-variance minimization, and (iii) merging regions considering human perception. Details of this merge stage are discussed as follows.

3.3.1 Merging on the Basis of T-Test

Some of the regions may be splitted due to the hard partitioning technique in the split stage, though they are the parts of the same object. Any two connected regions are qualified to be merged if they are both stable. These two regions are merged if they are within the 99% fiducial limit of T-test. A region is chosen to merge with another region if they have the minimum combined variance. This process will continue until there is a region that satisfies the merging criteria. The regions obtained after completing the merge on the basis of T-test are stable in nature. They may either be a full object or be a stable part of an object. To merge the stable components of an object another technique is applied which is detailed in the next Section.

3.3.2 Merging for Inter-variance Maximization and Intra-variance Minimization

As mentioned above, there may remain some stable regions, each of which are composed of pixels representing any stable part of an object. As there exists a huge number of objects having different variations among them, these objects are only differentiable if they have different appearance and visually distinct from each other. Since the number of clusters is neither fixed nor manually provided, the minimization of the intra-region variability and the maximization of the inter-region variability in the union of two regions are considered in the proposed algorithm like [16]. However, both the straight minimization of the intra-region variability and the maximization of the inter-region variability lead to undesirable trivial solutions being N regions or 1 region respectively. BIS minimizes the intra- region variability while at the same time constraining the inter region variability in the union of two regions. The reason behind such condition is - if two regions belong to single object, their intensities should be similar and as a result their combined variability should be minimal. On the other hand, when one of nearly intensified region disappears due to merging, the verity of variance is increased while the number of the regions is decreased. This leads to maximization of inter-region variability. Thereby, in the overall image, the inter-variance of object is maximal as they are distinctive from each others. This idea is applied on the remaining regions that need to be merged. This task terminates when no more region can be merged under this criteria.

3.3.3 Merging Regions Considering Human Perception

Even though the splitted regions are merged applying T-test first and then inter- and intra-variance, this may produce some parts of an object as a separate region and hence motivated to consider the human perception for merging as the final merging step. Form the theory it has been seen that, if the change of any object or feature is less than or equal to $0.5dB$, then human perception is unable to detect the change [1]. Considering the change of size in light of the above theorem it can be stated that, when any two connected regions are found where the size of any one object is less than or equal to 6% of other, then these two regions are merged to form a single region as a segmented object. This concept is applied at the last step of merging to merge smaller stable regions with their neighboring connected larger region to avoid hedge on the boundary of the identified objects. This gives better shape and look of identified objects.

3.3.4 The BIS Algorithm

To represent the algorithm formally let us assume the image (R) is defined by a set of regions $R = R_1, R_2, \ldots R_n$ where n > 0 and each region R_i contains a set of pixels whose pixel intensity is defined in set X_i, where $X_i = x_{i1}, x_{i2}, \ldots x_{id}$ where d > 0, μ_i is the average pixel intensity of region R_i. Connected(R_i, R_j) = 1 if the region R_i and R_j are connected. The pseudo code of the proposed BIS algorithm is given below. In this algorithm, firstly the image is resized (Step 1) and then split into 12 equal regions using T-test in Step 2. Then the image is recursively splitted into four regions, if the regions are seemed to be unstable using T-test and then R_{map} is constructed in Step 4. Algorithm finds out the accepted, partially accepted, and rejected regions in Step 5. Merge two regions if they proved to be stable by applying T-test followed by applying intra-variance and inter-variance test for merging while the remaining regions are merged by applying human visual perception in Step 6.

Algorithm 1. *BIS algorithm*
Pre condition: Objects to be segmented. **Post condition:** Segmented results 1. Resize image to 1024×768. 2. IF Image is unstable using T-test, split Image into 12 equal regions (Section 2.1). 3. Recursively split region R_i into four equal regions if it is unstable using T-test, $\forall$ i. 4. Construct R_{map} having the size of the image 5. Find accepted and rejected regions based on the predefined thresholds 6. Merge the regions according to Section 3.3. 7. Return segmented results

4 Computational Complexity

The time complexity of the BIS algorithm, which is detailed in Section 3.3.4, is presented below in a step-wise approach.

Step 1: The time required to resize image into a 1024×768 size image is $O(n)$, where n is the number of pixels in the image.
Step 2: Computational time required for checking image stability using T-test is $O(n)$.
Step 3: In the worst case, the computational time required to split the image is $O(1) \times O(n) = O(n)$.
Step 4: To calculate the R_{map} which is used to map the pixels into a region, requires $O(n)$ computational time.
Step 5: Step 5 will run for $O(n)$ computational time.
Step 6 : Region stability test using T-test requires $O(n)$ time and to merge regions with n pixels requires $O(n)$ time. The computation time required to compute the $\max Var$ for a image containing n pixels is $O(n)$ while the T-test needs $O(n)$ time. To examine a region whether it is less than 6% of another region requires $O(n)$ time. So, total time requires for this step is $O(n)$ time in the worst case.

Finally total computational time required for BIS algorithm is $O(n)+O(n)+O(n)+O(n)+O(n)+O(n)=O(n)$ in the worst case.

5 Experimental Results

In order to evaluate the performance the BIS algorithm, results obtained from the proposed BIS algorithm are compared with the results of OSF [1], ROSSM [12] and PSM [7] algorithms which all are implemented using MATLAB 7.1. A total of 210 different natural and synthetic gray-scale and color 2-D images were randomly selected for the experimental analysis, comprising up to 5 different regions (objects) having varying degrees of surface variation from the internet and IMSI. The detailed implementation procedures are provided in [7] and the original and manually segmented reference regions of the test images used are shown in **Figures 1 and 2.** To provide a better visual interpretation of the segmented results, both the reference and the segmented regions are displayed in different colors rather than their original gray-scale intensities.

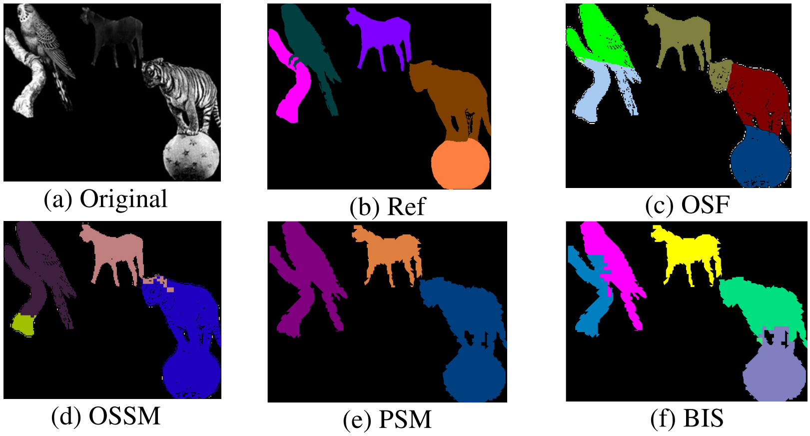
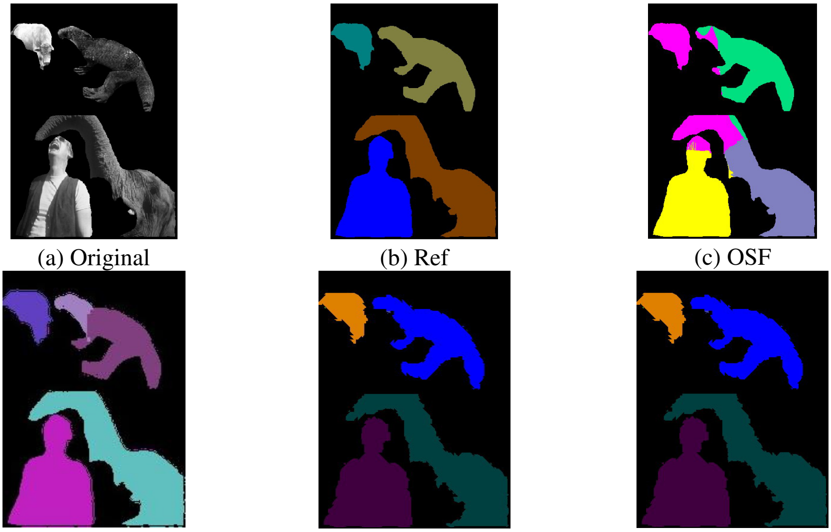


Fig. 1. Tiger image: (a) original image, (b) manually segmented reference image, and segmented results using (c) OSF, (d) OSSM, (e) PSM, and (f) BIS

Now we present an image with five different objects, some of them are connected while some are not, shown in Figure 1. The original synthetic image is presented in Figure 1(a) and the manually segmented image is illustrated in Figure 1(b). We can see that the performance of the BIS (Figure 1(f)}) algorithm is better then the OSF (Figure 1(c)), OSSP (Figure 1(d)) and PSM (Figure 1(e)) algorithms in terms of misclassification error rate and visual analysis.

The segmented images of an elephant image is shown in Figure 2. The original and manually segmented images are displayed in Figure 2(a) and (b) respectively. This image consists of four different objects and the objects are not connected. The BIS (Figure 2(f)) algorithm performs better than any other algorithm with almost zero misclassification error. A small amount of error introduced because the boundary blocks are replaced by predefined patterns. Since the regions or objects are not connected PSM (Figure 2(e)) algorithm performs same as the BIS algorithm. The segmentation performance of OSF (Figure 2(c)) and OSSM (Figure 2 (e)) algorithm is very bad with a high misclassification error rate.

In assimilating the overall segmentation performance of the proposed segmentation algorithm, it needs to be highlighted that only the best results for each segmentation algorithm (OSF, OSSM and PSM) are considered. These three were compared with



(a) Original (b) Ref (c) OSF

(d) OSSM (e) PSM (f) BIS

Fig. 2. Elephant image: (a) original image, (b) manually segmented reference image, and segmented results using (c) OSF, (d) OSSM, (e) PSM, and (f) BIS

the BIS algorithm. Of the 146 test images, BIS produced superior results for 106 images. For the remainder of the images, OSF, OSSM and PSM provided better results for only 45, 47, and 22 images respectively**.**

6 Conclusion

This paper has proposed a new segmentation approach called block based image segmentation (BIS) algorithm to address some of the limitations inherent with the PSM algorithm. The BIS algorithm as like PSM algorithm firstly splits the image into several regions until the region stability is achieved or the block size becomes 16X16**.** Then the splitted regions are matched with the micro-block (MBs) to produce accepted and rejected regions. Then the accepted and connected splitted regions are merged using multistage merging techniques, such as T-test, intra-variance and inter-variance test, and human visual perception techniques. Experimental results have shown that the newly developed BIS algorithm has been able to segment connected images well and outperforms the pattern based object segmentation using split and merge (PSM), object based image segmentation using fuzzy clustering (OSF) and Robust Image Segmentation Based on Split and Merge (OSSM). This will be highly applicable in low bit rate video coding applications for real life application where some misclassification error is acceptable. A little shape distortion occurs due to pattern matching in 16X16 size regions in the BIS algorithm.

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